

Extended Reliable Robust Motion Planners

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joint work with **Alexandre Chapoutot**², **David Filliat**²

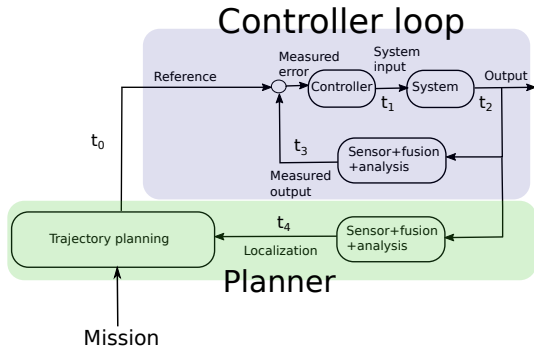
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March 28, 2017

Introduction

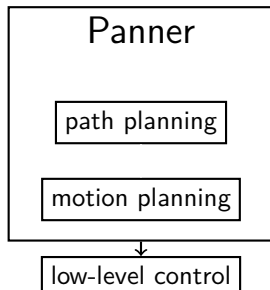
Autonomous vehicle



Goal of the project:

- ▶ understand main pieces of the system
- ▶ validate their behaviour
- ▶ validate the behaviour of the overall system.

A hierarchical control



- ▶ **Path planning** generates a set of way points (does not take into account the dynamics of the vehicle) from a map (totally or partially) known, take into account obstacles (static)
- ▶ **Motion planning** generates a set of trajectories feasible for the dynamics considered and take into account obstacles (static and/or dynamic)
- ▶ **Low-level controller** tries to follow the (discretized) trajectory w.r.t. the dynamic of the vehicle

We focus on sampling-based **motion planning algorithms** :

- ▶ Rapidly-exploring Random Trees (**RRTs**) and
- ▶ Optimal Rapidly-exploring Random Trees (**RRT***).

Take into account

- ▶ A model of the vehicle,
- ▶ A model of a map with obstacles (static),
- ▶ Uncertain information on the position/orientation, etc. - bounded within *interval vectors* or *boxes*.

This talk

Propose new methods to plan guaranteed to be safe paths:

- ▶ improved BoxRRT - **rciBoxRRT**,
- ▶ improved BoxRRT - **csiBoxRRT**,
- ▶ new algorithm based RRT* - **t(towards)BoxRRT***.

The BoxRRT is based on

Reliable robust path planning. Romain Pepy, Michel Kieffer, Eric Walter. Journal Applied Mathematical Computing. 2009.

Box-RRT Algorithm

Goal

- ▶ “quickly” find a path going from an initial configuration \mathbf{s}_i to a final configuration \mathbf{s}_f
- ▶ while avoiding obstacles \mathbf{s}_o
- ▶ and taking into account bounded uncertainties.

Main ingredients

- ▶ model of the vehicle
- ▶ based on RRT Algorithm
- ▶ combined with interval analysis tools (e.g., guaranteed numerical integration)
- ▶ applied with
 1. a random (**rciBoxRRT**) and
 2. a designed control input (**sciBoxRRT**)

First improvement : use of modern and new tools for the guaranteed numerical integration

Implement these algorithms with **DynIBEX**.

A library combining of **Constraint Satisfaction Problems solver** (IBEX¹) with **validated numerical integration methods** à la Runge-Kutta.

Three temporal constraints have been used:

- ▶ stay in state-space;
- ▶ has crossed (in negative form) obstacles;
- ▶ one in target;

and one contractor on tube has been used

- ▶ get tight(t) to get final state.

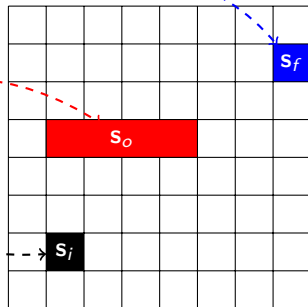
So these algorithms can be quickly implemented in DynIBEX.

¹Gilles Chabert (EMN) et al. <http://www.ibex-lib.org>

How does rciBoxRRT–sciBoxRRT work?

Initialization

- ▶ A discretized map
- ▶ A final state
- ▶ Some obstacles
- ▶ An initial state
- ▶ A tree of possible trajectories



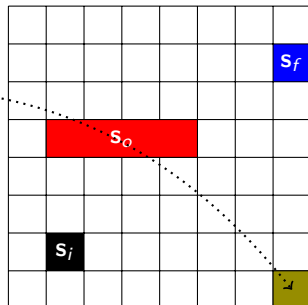
How does rciBoxRRT—sciBoxRRT work?

Iteration 1

The building of the tree follows
3 main steps in a loop

1. Pick s_{random}
2. Find s_{nearest}
3. Compute s_{new}

until s_f is reached



Choose randomly a free state of
the map



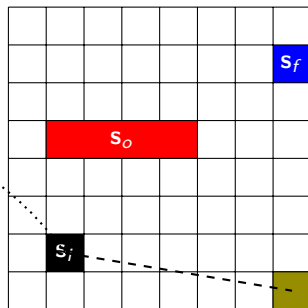
How does rciBoxRRT—sciBoxRRT work?

Iteration 1

The building of the tree follows
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Find the nearest node in the tree
following a Hausdorff distance
between two boxes



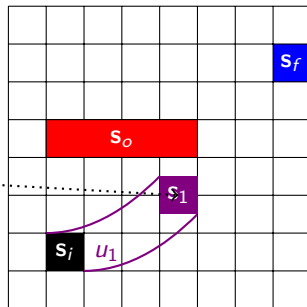
How does rciBoxRRT—sciBoxRRT work?

Iteration 1

The building of the tree follows 3 main steps in a loop

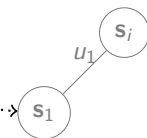
1. Pick s_{random}
2. Find s_{nearest}
3. Compute s_{new}

until s_f is reached



Predict the next state from a **random** or **designed** control input u

if no collision detected add $(s_{\text{nearest}}, u, s_{\text{new}})$ in the tree



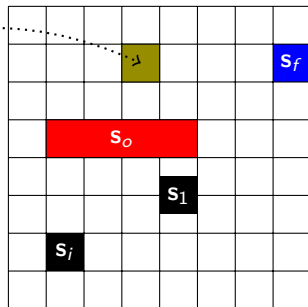
How does rciBoxRRT—sciBoxRRT work?

Iteration 2

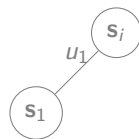
The building of the tree follows
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1. Pick s_{random}
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3. Compute s_{new}

until s_f is reached



Note that the choice of s_{random} is biased to increase probability to be closer to s_f (*Random box BiasGoal procedure*)



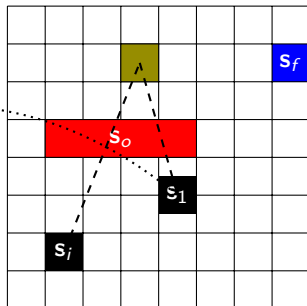
How does rciBoxRRT–sciBoxRRT work?

Iteration 2

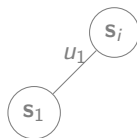
The building of the tree follows
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Computing distances has a linear complexity w.r.t. the number of nodes in the tree



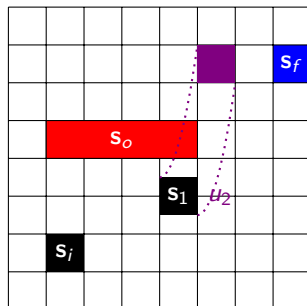
How does rciBoxRRT—sciBoxRRT work?

Iteration 2

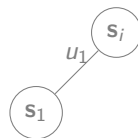
The building of the tree follows 3 main steps in a loop

1. Pick s_{random}
2. Find s_{nearest}
3. Compute s_{new}

until s_f is reached



The absence of collision is detected when the **tube** does not intersect an obstacle



tBoxRRT* Algorithm

RRT* Algorithm

- ▶ "quickly" finds a "low cost" path going from an initial configuration \mathbf{s}_i to a final configuration \mathbf{s}_f
- ▶ while avoiding obstacles \mathbf{s}_o

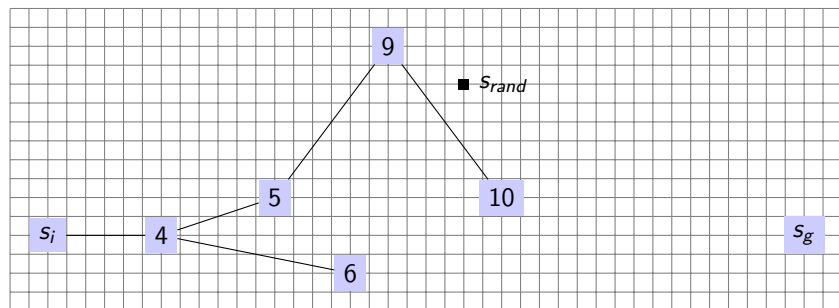
Based on :

Sampling-based algorithms for optimal motion planning. S. Karaman and E. Frazzoli. The international journal of robotics research. 2011.

tBoxRRT* Algorithm

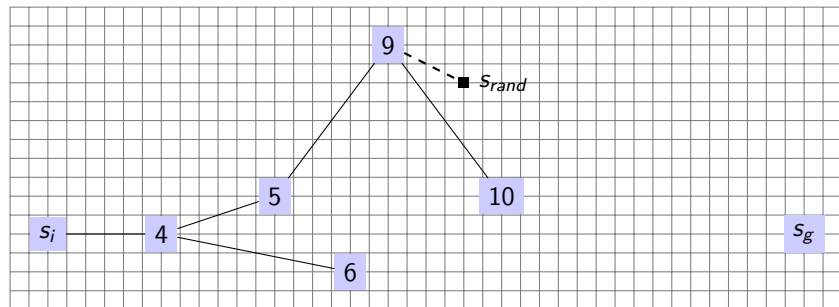
- ▶ based on RRT* Algorithm : finds a "low distance" path going from an initial configuration $[\mathbf{s}_i]$ to a final configuration $[\mathbf{s}_f]$,
- ▶ combined with interval analysis tools (e.g., guaranteed numerical integration)
- ▶ while avoiding obstacles \mathcal{S}_{obs}

How does tBoxRRT* work?



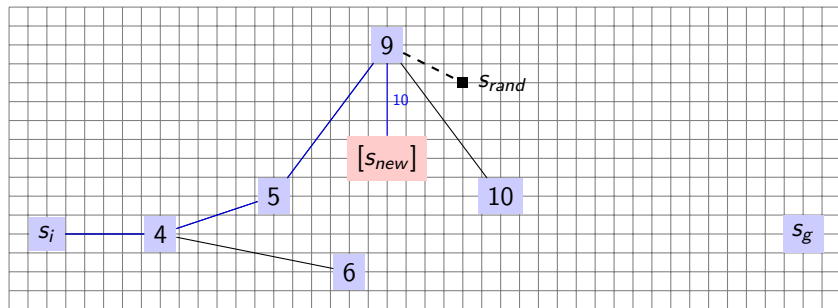
- ▶ $[s_{rand}] \leftarrow \text{random-box-GoalBias}$;
- ▶ Values inside the vertices : distance (e.g. the Hausdorff distance between two boxes) from the initial state to that vertex.

How does tBoxRRT* work?



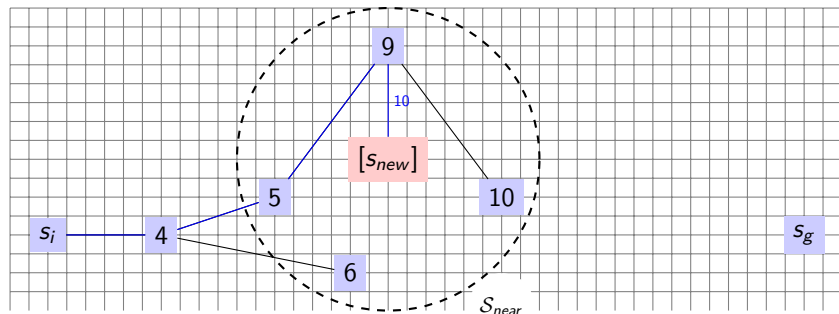
- ▶ $[s_{nearest}] \leftarrow \text{nearest-neighbor}(G, [s_{rand}]);$
- ▶ Nearest-neighbor procedure uses the Hausdorff distance between two boxes metric.

How does tBoxRRT* work?



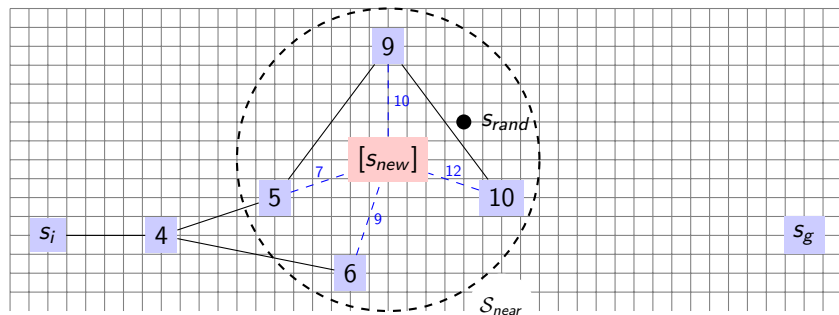
- ▶ $([s_{new}], u) \leftarrow \text{steer}([s_{nearest}], [s_{rand}])$
- ▶ 1. u is computed using a desired objective.

How does tBoxRRT* work?



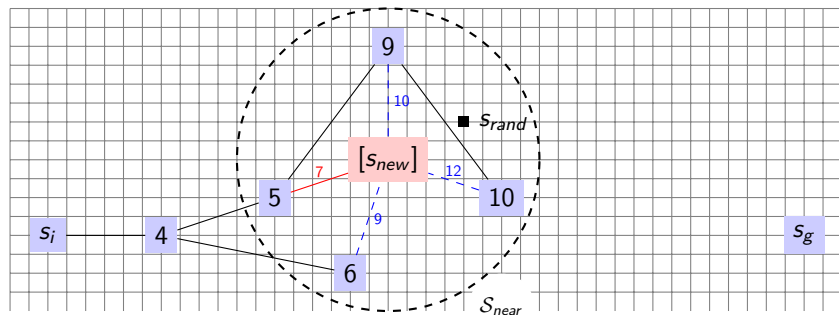
- ▶ $S_{near} \leftarrow \text{near}(G, [s_{new}])$
- ▶ Near procedure : uses **k-nearest neighbors algorithm** (all vertices within the area of a ball of radius $r(n) = \gamma \log(n)$ with $\gamma = 2\epsilon$ (ϵ : Euler's number; n : number of vertex in the tree at an iteration))

How does tBoxRRT* work?



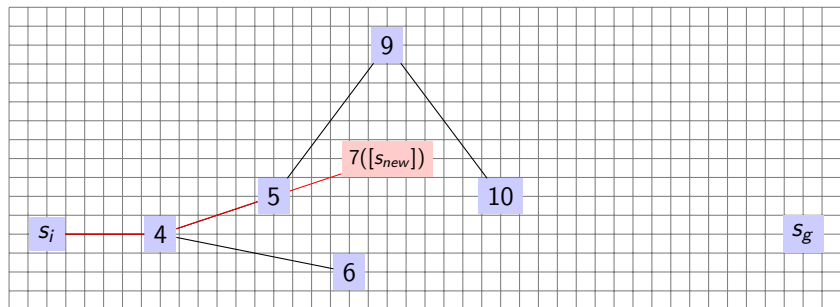
- ▶ $[s_{min}] \leftarrow \text{ChooseParent} (S_{near}, [s_{nearest}], [s_{new}])$

How does tBoxRRT* work?



- ▶ $[s_{min}] \leftarrow \text{ChooseParent} (\mathcal{S}_{near}, [s_{nearest}], [s_{new}])$

How does tBoxRRT* work?



- ▶ $G \leftarrow \text{rewire}(G, [s_{min}], [s_{new}])$

Until

- ▶ *max iteration number is reached or*
- ▶ *a solution is found (e.g. $[s_{new}] \neq \emptyset, [s_{new}] \subset \text{Int}([s_{goal}])$)*

tBoxRRT* Algorithm

```
input :  $[s_{init}], [s_{goal}], K$ ;  
output :  $G = (V, E)$ ;  
 $G.init([s_{init}]);$   
 $i \leftarrow 0$  ;  
repeat  
   $[s_{rand}] \leftarrow \text{random-box}(i)$   
   $[s_{nearest}] \leftarrow \text{nearest-neighbor}(G, [s_{rand}])$   
   $([s_{new}], u) \leftarrow \text{steer}([s_{nearest}], [s_{rand}])$   
  if collision-free-path( $[s_{new}]$ ) then  
     $S_{near} \leftarrow \text{near}(G, [s_{new}], V)$   
     $[s_{min}] \leftarrow \text{ChooseParent}(S_{near}, [s_{nearest}], [s_{new}])$   
     $G \leftarrow \text{rewire}(G, [s_{min}], [s_{new}])$   
  end if  
until  $(i++ < K)$  or  $([s_{new}] \neq \emptyset, [s_{new}] \subset \text{Int}([s_{goal}]))$   
return  $G$ 
```

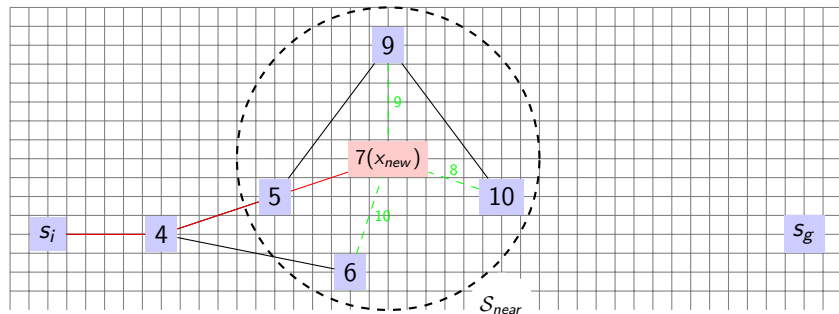
Algorithm 1: BoxRRT* motion planning algorithm

BoxRRT* Algorithm - Future work

```
input :  $[s_{init}], [s_{goal}], K$ ;  
output :  $G = (V, E)$ ;  
 $G.init([s_{init}])$ ;  
 $i \leftarrow 0$  ;  
repeat  
   $[s_{rand}] \leftarrow \text{random-box}(i)$   
   $[s_{nearest}] \leftarrow \text{nearest-neighbor}(G, [s_{rand}])$   
   $([s_{new}], u) \leftarrow \text{steer}([s_{nearest}], [s_{rand}])$   
  if collision-free-path( $[s_{new}]$ ) then  
     $S_{near} \leftarrow \text{near}(G, [s_{new}], V)$   
     $[s_{min}] \leftarrow \text{ChooseParent}(S_{near}, [s_{nearest}], [s_{new}])$   
     $[s_{min_k}] \leftarrow \text{ChooseChildren}(S_{near} \setminus \{[s_{min}]\}, [s_{new}], [s_{nearest}])$   
     $G \leftarrow \text{rewire}(G, [s_{min}], [s_{new}], [s_{min_k}])$   
  end if  
until  $(i++ < K)$   
return  $G$ 
```

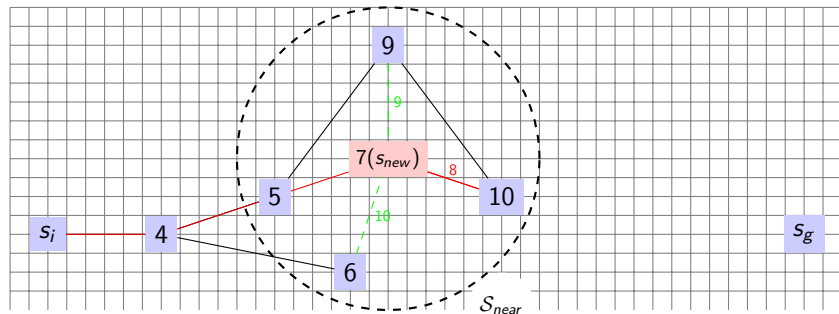
Algorithm 2: BoxRRT* motion planning algorithm

How does ChooseChildren procedure work?



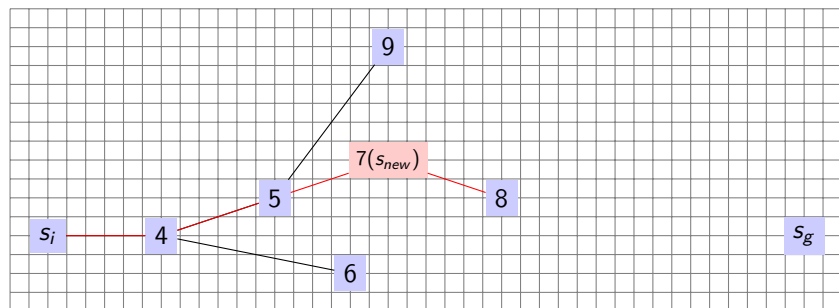
- ▶ $[S_{min_k}] \leftarrow \text{ChooseChildren}(S_{near} \setminus \{[S_{min}]\}, [S_{new}], [S_{nearest}])$

How does ChooseChildren procedure work?



- ▶ $[S_{min_k}] \leftarrow \text{ChooseChildren}(S_{near} \setminus \{[S_{min}]\}, [S_{new}], [S_{nearest}])$

How does ChooseChildren procedure work?



► $G \leftarrow \text{rewire}(G, [s_{min}], [s_{new}], [s_{min_k}])$

Future work :

Until the max iteration number is reached.

Apply the A* method and find the shortest path?

Cinematic of a Mobile Robot in 2D

We consider a simple car model

$$\dot{x} = v \cos(\theta)$$

$$\dot{y} = v \sin(\theta)$$

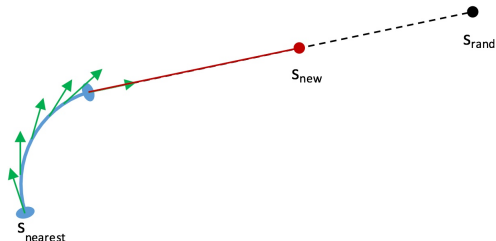
$$\dot{\theta} = \frac{v}{L} \tan(\delta)$$

with constraints

- ▶ $v \in [-1, 1]$ - longitudinal speed and
- ▶ $\delta \in [-\pi/2, \pi/2]$ - steering angle.
- ▶ $L = 1.5[m]$ - distance between the front and back axes of the car.

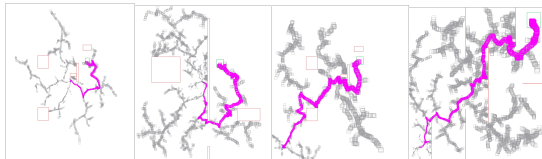
Control input for the simple car model

- ▶ **rciBoxRRT** : control input randomly chosen in the admissible set.
- ▶ **sciBoxRRT** and **tBoxRRT***: control input designed in two steps:



Results: 4 environments

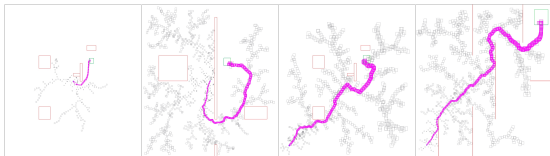
- ▶ ***rciBoxRRT*** (2200t.v.:28[s]; 5880 t.v.:103[s]; 3416t.v.:51 [s]; 7802t.v.:141[s]).



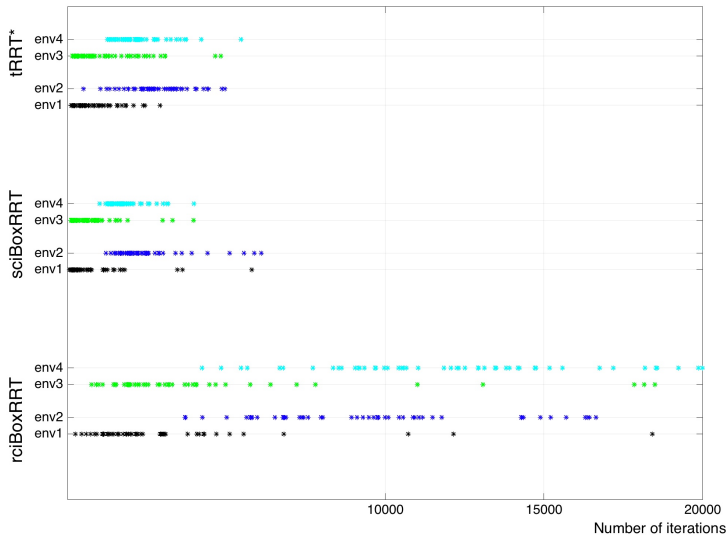
- ▶ ***sciBoxRRT*** (570 t.v.:11 [s]; 1149 t.v.:32 [s]; 278 t.v.:5[s]; 978 t.v.:26[s]).



- ▶ ***tBoxRRT**** (156 t.v.:3 [s]; 1088 t.v.:38 [s]; 786 t.v.:20 [s]; 963 t.v.:28[s]).

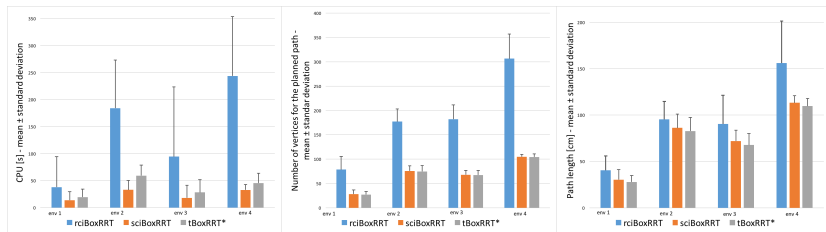


Results: rciBoxRRT, sciBoxRRT and tBoxRRT*



Results: rciBoxRRT, sciBoxRRT and tBoxRRT*

- ▶ Computational time (s) required by the three proposed algorithms for convergence,
- ▶ Number of vertices for the planned path obtained by the three proposed algorithms,
- ▶ Planned path length (cm) obtained by the three proposed algorithms.



Conclusion

- ▶ Shown three motion planner algorithms in the control hierarchy: rciBoxRRT, sciBoxRRT and tBoxRRT* (Submitted to CDC17)
- ▶ Presented a small example of autonomous vehicle

Future work

- ▶ Propose the BoxRRT* (maybe use the A* method for the shortest path search)
- ▶ BiBoxRRT* : based on RRT Algorithm with two trees : one growing from \mathbf{s}_i and the other one from \mathbf{s}_f until they intersect ?
- ▶ Combine Box-RRT with low-level controller (PID)

Acknowledgment

Thanks to

- ▶ **Olivier Mullier, Julien Alexandre dit Sandretto,**
(U2IS, ENSTA ParisTech, Palaiseau, France)
- ▶ **Eric Goubault and Benjamin Martin,**
(LIX, Ecole Polytechnique, Palaiseau, France)

for productive and useful discussions.

Thank you !